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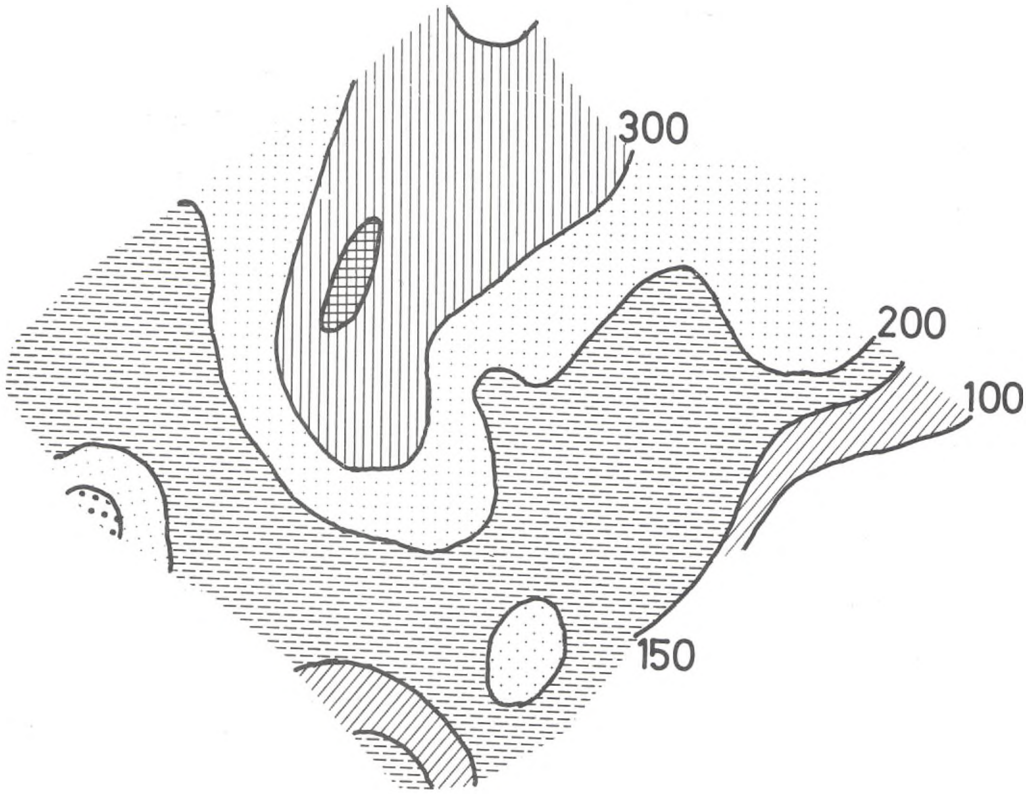

PROBLEMS IN IDENTIFYING DISTRIBUTION PATTERNS OF OCEANOLOGICAL PARAMETERS

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Problems in identifying distribution patterns of oceanological parameters

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PREFACE

This paper is based on a lecture given by Dr. L. Postel, Rostock, GDR, at an ICES Workshop on Patchiness Studies in the Baltic in Tallinn, Estonian SSR, 21-23 March, 1983. It summarizes important aspects on theoretical-practical problems encountered by scientists dealing with the heterogeneity of marine parameters in space and time.

As a follow-up of the Workshop an international Study Group under the auspices of ICES was established in order to coordinate joint "patchiness" studies in the Baltic, and this paper is intended to form an important part of the basis for the discussions within the Group.

Bernt I. Dybern
Convener of the Study Group

ABSTRACT

The dynamics of an ecosystem consist of an assemblage of processes with very specific spatial and time scales ranging from seconds to thousands of years and from a few centimetres to a few thousand kilometres.

If, as usually the case is in field studies, the object being studied cannot be isolated from its environment, it is generally embedded in a complex mixture of processes. Measured data, even if they involve only a single parameter, often represent superpositions of data stemming from a variety of processes.

Desired signals can be isolated, or undesirable information can be suppressed, by filtering in time or space. Depending on the scale in which the process being studied takes place, the fil-

ter used must be of the high-pass, low-pass or band-pass type. Either of two basic approaches may be used:

At the experimental design stage a certain degree of isolation may be achieved by incorporating an appropriate sampling filter; this involves mainly the choice of appropriate measuring lengths and invervals.

At the data handling stage, on the other hand, the use of mathematical filter operations is appropriate. Mathematic filters can also be used in the reverse mode as inverse filters to eliminate modifications of a real phenomenon such as those caused by the undesirable effects of a sampling filter.

During the experimental design stage it is also necessary to take into account the fact that the distribution of the properties being measured may be anisotropic.

Data analysis involves handling the measured ecological data by methods that are suitable for handling random functions that vary in time and space.

INTRODUCTION

Biological oceanographers have been confronted with the problem of heterogeneity in distribution patterns especially since the mid-seventies. Comparative investigations in different habitats have made it necessary to consider the comparability of the scales of the different phenomena being observed. Many review papers have since been published. One of the most extensive is "Spatial patterns of plankton communities", edited by Steele (1978). It deals with the observation of patchiness, data management and initial theoretical formulations. Here I will consider two sides of these problems, firstly the space-temporal character of distribution patterns in general, and, secondly, the problem of their identification.

THE SPACE-TEMPORAL CHARACTER OF DISTRIBUTION PATTERNS

I have chosen plankton distribution as an example. Its heterogeneity has been known for more than 80 years, since Haeckel's critique of Hensen's contrary opinion. Our understanding of patchiness stems from a variety of different extensive and intensive observation programmes. We think, for instance, of the German Atlantic Expedition of RV "Meteor" in the nineteen-twenties. For the first time this expedition covered a large area with a rough observation grid between approximately 15° N and 60°S. Meridionally, the distances between the stations were about 700 km and zonally they were about 350 km. The most interesting planktological results were of a biogeographical character (Hentschel and Wattenberg, 1930). Later our knowledge in the so called coarse- and mesoscale range of the distribution spectrum increased as a result of, for instance, the intensive CalCOFI-programme[1], which has been going on off California since 1949 to the present day and which has thus lasted over 30 years. Measurements have been carried out every one to three months in a grid with a size of between 30 km and 60 km (Owen, 1980). The results show the importance of the choice of the measuring length and interval for the kind of distribution patterns observed.

Progress in development of instruments has allowed a further shortening of the measuring intervals. Since the 'thirties' the continuous plankton recorder (CPR) of Hardy (1939) has permitted the mesoscale analysis of plankton patterns. Today we have electronic devices working with high resolution and more or less continuously in the fine scale range. The Canadian "Batfish" can differentiate plankton qualitatively into the main groups and allows the simultanous measurements of environmental parameters, such as CTD and flourescence (Herman and Dauphinee, 1980).

Both the shortening of measuring intervals and the existence of long data series (e.g. Colebrook, 1978) have confirmed the observation that data vary in space and time. In contrast to simple statistics based on random samples which are independent

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[1] CalCOFI = California Cooperative Oceanic Fisheries Investigation

of each other, we here find correlations between the data. Such autocorrelations (synonymous terms are persistence or trend) are often indicated by a characteristic sequence of the data. In general they depend more on time and space than on chance. This leads to dynamic considerations: we no longer speak of a random sample, but of a random function or a stochastic process.

Data that vary in time and space can be correctly managed by means of a special theory of such processes which is part of the probability theory. Spectra analysis is one of the special techniques and is used to investigate the variability of, for instance, plankton in time and space (cf. Platt and Denman, 1975; Walsh et al., 1977; Mackas and Boyd, 1979).

Certain phenomena producing distribution patterns have significant or characteristic time and space scales. This forms the basis for the dependence of data on time and space. Inter- and intraspecific relations of zooplankton (species), for instance, generally act in the range from 10 to 100 m and produce distribution patterns of the same scale. On the other hand, all plankton communities of the whole Baltic are influenced by seasonal signals or climatic changes.

We note: the whole dynamics of an ecosystem forms an ensemble, a mixture, of processes covering a wide range of scales. Within the reference frame of these scales they produce significant patterns ranging in duration from seconds to thousands of years and from centimetres to thousands of kilometres.

This is illustrated by Haury et al. (1978), by means of a schematic diagram (Fig. 1, after text). They used amplitudes in zooplankton biomass variability as an estimation of the ecological importance of different scales. The authors were unable to take into account the fact that phenomena may be superimposed, so that smaller-scale features may depend on the phases of large scale phenomena. This kind of persistence in a scale-dependent data set is caused by a further dependence on time and space of superimposed features. In this manner climatic changes can modify, for example, the seasonal variability of plankton biomass, or smaller scale variations caused by Rossby waves may be masked by seasonal signals. Such processes are defined as instationary stochastic processes and must be taken into account during data analysis (cf. Taubenheim, 1969).

Haury's diagram also shows that there is no close linear correlation between the dimensions in time and those in space. Consider, for instance, the diurnal rhythm. It can be observed in all spatial scales. Similarly, patchiness caused by oceanic front width occurs in most time scales. This makes it difficult to define corresponding scales in time and space.

The table below shows definitions given by Radach and Mann (1981):

Space-scales		*Time-scales*	
Mega scale	>3,000 km	Climatic scale	>few years
Macro scale	1,000-3,000 km	Meso scale	few months-few years
Meso scale	100-1,000 km	Seasonal scale	1 year
Coarse scale	1-100 km	*Weather-scale*	few days-1 year
Fine scale	1-1,000 m		
Micro scale	1-100 cm	*Diurnal-scale*	1 day

Further one can categorize generating and maintenance mechanisms for patchiness in the pelagic area of the Baltic Sea in accordance with the earlier work by Haury et al. (1978) (Fig. 3 after text). Generating and maintenance mechanisms are classified into physico-chemical and biological ones. Scales are estimated very roughly, and in some cases they have yet to be given completely. Spatial scales of biological phenomenons are estimated by the habitat dimensions of the different organism groups.

PROBLEMS IN IDENTIFYING DISTRIBUTION PATTERNS

If a feature of interest is observed in field studies, it is impossible to isolate it from influences of other environmental parameters. In other words, we are dealing with a complex of interactions and the data reflect the above-mentioned superposition. If we wish to analyse single features, separation is necessary. This can be done in two ways. A certain degree of isolation can be achieved already when designing field studies by choosing a characteristic sampling filter. At the data analysis stage we can use mathematical filter operations as well as other techniques, such as the separation of data variability by spectral analysis, for the same purpose.

An important sampling filter is the observation of a characteristic sector of the distribution spectrum in time or space of the quality being studied. This can be performed by the choice of a suitable measuring length and interval. Both categories define the spectral sector (synonymous terms are observational window or band width).

The sector is limited by measuring length to the low frequency or wave number range, i.e. to the side of the observational window with longer periods or wavelengths. The opposite side is limited by the measuring interval.

These terms are related to spectral theory, and I shall therefore give a few brief comments on the spectral analysis method before continuing the discussion about sampling filters.

In spectral analysis it is common to divide the total variability of a recording into single sinoid or cosinoid curves of certain periods or wavelengths and to calculate their amplitudes. Distinct periods or wavelengths represent significant variations or patterns, and thus correspond to a generating mechanism as mentioned above. To illustrate this principle I have taken an example from Walsh et al. (1977). These authors produced an artificial recording of wind velocity in an upwelling area of the Eastern Boundaries (Fig. 2 A). It consists of the seasonal signal of 365 d, the so called "event scale", a characteristic change in upwelling and relaxation with a period of 14 d, and a diurnal signal of 1 d. The spectral analysis produces 3 discrete lines into which the total variability is divided (Fig. 2 B). The amplitude of a line represents the relative importance of the single feature inside the observational window. However the spectra of real recordings consist rather of curves than of discrete lines, and their variability is distributed over the total width of the observational window. Peaks are found in that spectral range or in that scale, in which the most frequent variances are localized. They are related to systematic variations, and the remainder is related to random fluctuations produced, for example, by the noise stemming from an instrument or method being used. A typical example is a time series of zooplankton biomass measured in the Arkona Basin, in mid 1977 (Fig. 4 A). The dominant periods are approximately 1, 3, 4 and 7 days (Fig. 4 B). It must be noted, by the way, that spectra calculated by the maximum entropy method (Aurass et al., 1977), produce a certain predictive low frequency part.

We shall now return to our choice of measuring length and sampling interval as a sampling filter. The filter should exclude the possibility of obtaining information about the system at all frequencies or wave numbers outside this band. It must be remembered, however, that this method is associated with sampling effects. These could be excluded if we could obtain complete information regarding the stochastic process. But this is impossible: It would involve knowing all realizations of the process, and that would mean an infinite number of infinitely long data sets. In practice we have to interpret a finite number, which is usually one *finite* data set composed of *discrete* measurements. In other words, some information is lost, and this leads to two different effects:

The effect of data set limitation can lead to a trend in the data set; i.e. the spectrum may include a low frequency signal. It must be assumed right from the start that not all variations of different periods or wavelengths will be recorded, or that only a part of the low frequency oscillation will be observed.

A second effect is that of the equidistant, discrete measurements. This will in addition make it impossible to observe the behaviour of a stochastic process between the data points. Too long a sample interval will convert signals with periods or wavelengths shorter than the sample distances into low frequency variations. That means that these signals cannot be observed and will, moreover, produce an additional oscillation with longer periodicity (wavelength). This phenomenon is known as the *aliasing* effect. We must therefore check whether a data set is aliased or not by pilot investigations with shorter sampling intervals, if possible by continuous recording or at least by special, theoretical considerations.

To illustrate this we present an example used by Platt and Denman (1975): Consider a region with a large semidiurnal signal with a period of 13 h which influences the measured process. If a single station or two were sampled once a day, only an apparent cycle with a period of 6.5 days would show up in the data, as illustrated in Figure 5. There would be no indication of the actual 13 h periodicity. Even sampling once every 6 h, or more than twice during each semidiurnal signal, would still modulate the real periodicity, at first also with a further period of 6.5 days. The authors conclude that the sampling rate should be at least four samples per cycle for the shortest period fluctuation that may be present.

According to the Nyquist sample theorem a signal can be detected if its cycle (period or wavelength) is greater than twice the sampling interval.

Spectral methodology defines the measuring length. Using the maximum entropy method (Aurass et al., 1977) the signal should be included in the measuring length at least for 3 times, and using the power spectra method 10 recorded cycles are necessary.

These are important and also simple designing principles. Further sampling filters are the pecularities of instruments and the noise produced by imperfect field and laboratory work. There are preference scales of instrument efficiency, shown in Fig. 6. Special estimations of such filtering properties may lead to certain corrections for such influences by mathematical inverse filtration.

We shall now turn briefly to mathematical filter operations. Due to their qualities they suppress undesired information. In general and in categorizing mathematical filters too, it is necessary to distinguish between low pass, high pass and band pass filters.

Low pass filters suppress high frequencies and short periods while permitting low frequencies (longer periods) to pass. They are used if a low frequency signal, i.e. slow variations, is to be distinguished from high frequency noise, i.e. from rapid fluctuations. In the case of equidistant sample intervals it is possible to prevent the previously mentioned aliasing effect. This can be done, for instance, by statistical averaging, or this actually belongs elsewhere by using averaging sampling methods.

High pass filters produce the opposite result. They are therefore useful for suppressing slow variations, such as a trend, in the data set.

Data sets can be split into high and in low frequency parts by the complementary use of low and high pass filters.

Band pass filters have universal applications. In certain scales they have maximum permeability, and suppress variations outside this band. They are useful for isolating certain variations from the data material.

Particulars of the different filtering operations are given by Taubenheim (1969), Lass and Fennel (1979) and Chelton et al. (1982).

The Figure 7, finally, summarizes the main kinds of filter which convert "real patterns" into "observed patterns". At the bottom we have the criterion "sampling direction", i.e. the dependence of patterns on the main medium transport. There is no sampling direction if the property being studied is isotropic. In this case the property (biomass, individual number, species density, etc.) is equally distributed in all directions. But most patterns that have to be measured are anisotropic and are influenced by bottom topography, coastal configuration, discontinuity layers, frontal systems and so on. This is something that must also be taken into account when designing field programmes.

As a "last final" remark we should thus note that ecological processes vary in both time and space, and that data analysis has to take this fact into account.

ACKNOWLEDGEMENTS

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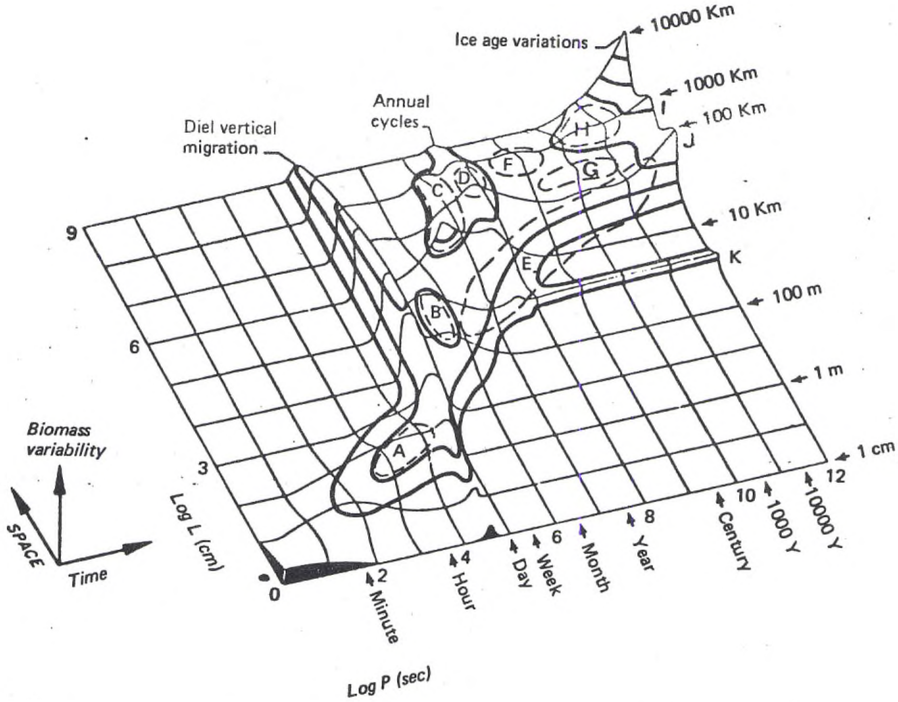


Fig. 1. A semi-quantitative three-dimensional representation of relative variability in zooplankton biomass over a range of time and space scales (from Haury et al., 1978). A - 'micro' patches; B - swarms; C - upwelling; D - eddies and rings; E - island effects; F - 'el nino'-type events; G - small ocean basins; H - biogeographic provinces; I - currents and oceanic front lengths; J - current widths; K - oceanic front widths.

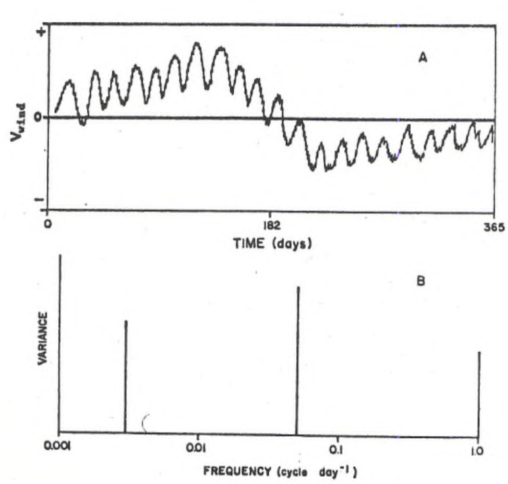


Fig. 2. Hypothetical time series (A) and frequency spectrum (B) of dominant scales of season, event, and variability of an upwelling ecosystem (from Walsh et al., 1977).

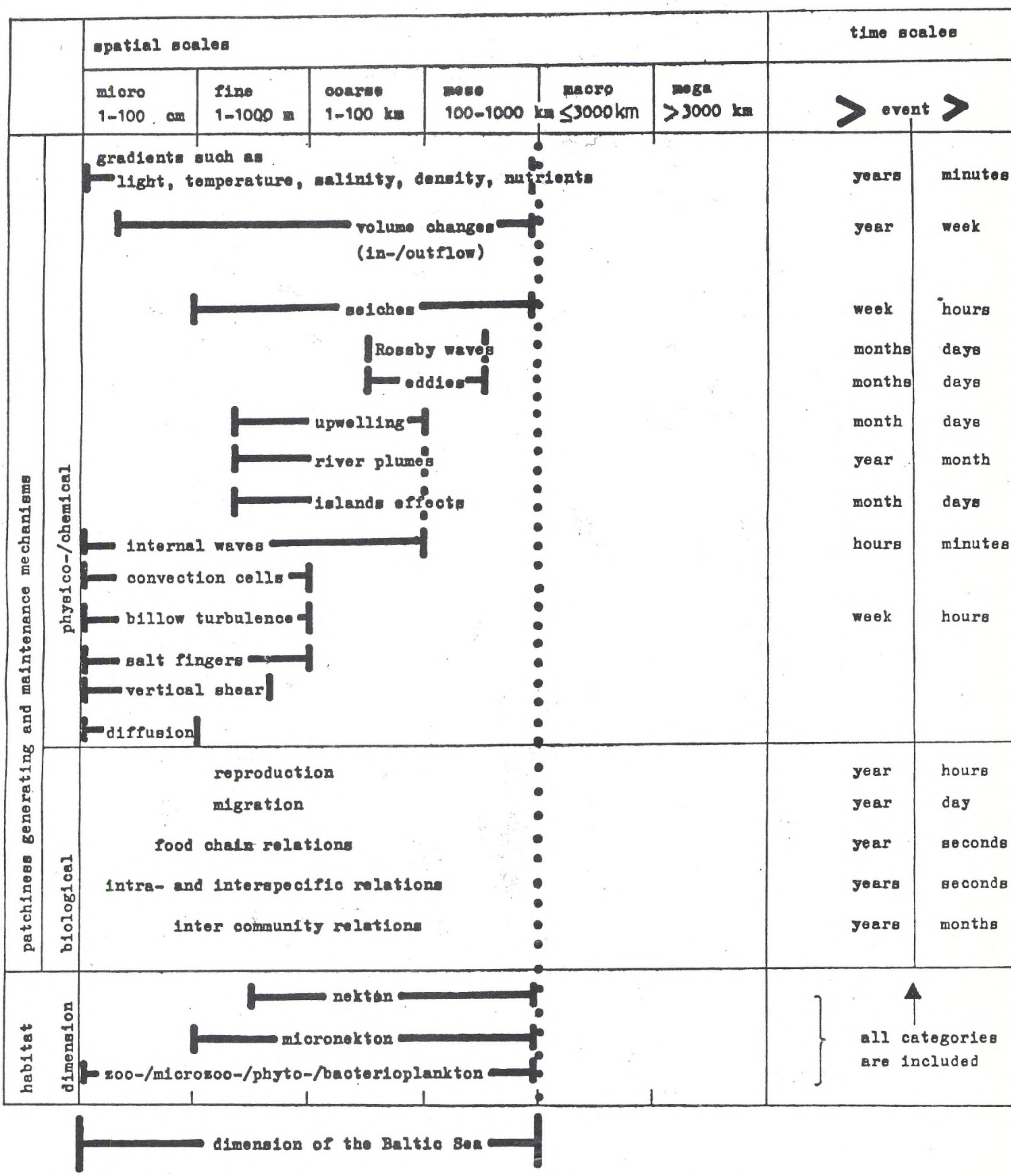
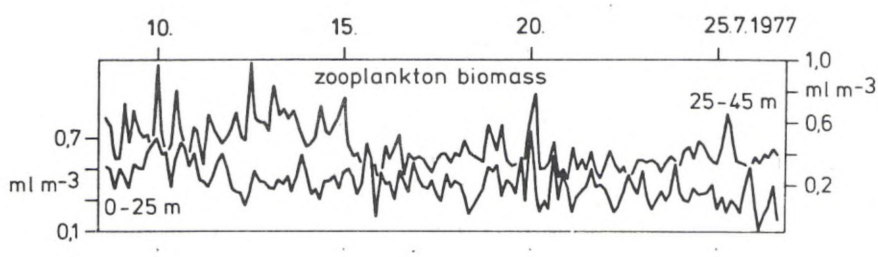


Fig. 3. Scales of generating and maintenance mechanisms for patchiness in the pelagial of the Baltic Sea (modified after Haury et al., 1978).



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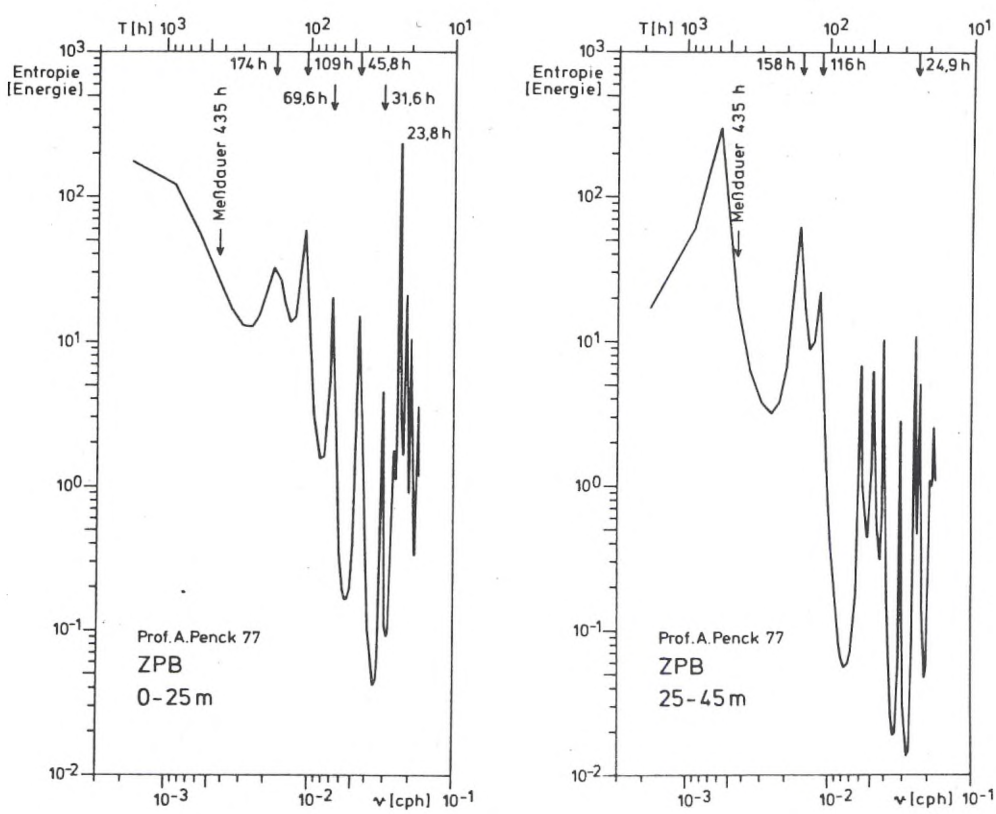

B

Fig. 4. Time series of zooplankton displacement volume (ZPB) measured in depth intervals of 0 to 25 m and 25 to 45 m, Arkona Basin, July 1977 with measuring length of 435 h and sampling interval of 3 h (from Breuel et al., 1978) (A), and pertinent maximum entropy spectra (B).
T = period, $\nu = \frac{1}{T}$ = frequency, Energie = energy, relative units, Meßdauer = measuring length.

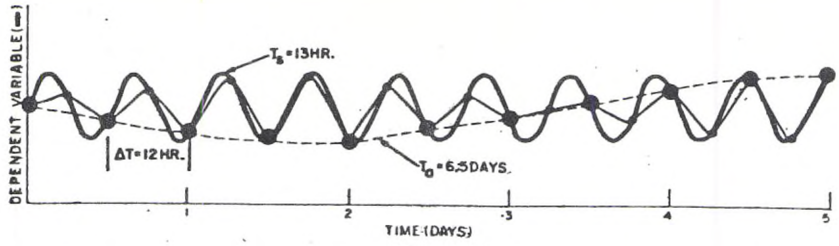

Fig. 5. An example of aliased sampling (from Platt and Denman, 1975). The heavy solid line represents the signal to be sampled with a period (T_s) of 13 h. The large dots represent discrete sampling at 12 h intervals, and the dashed line represents the apparent 6.5 day periodicity. The thin line connecting the large and small dots represents the apparent signal for a 6 h sampling interval.

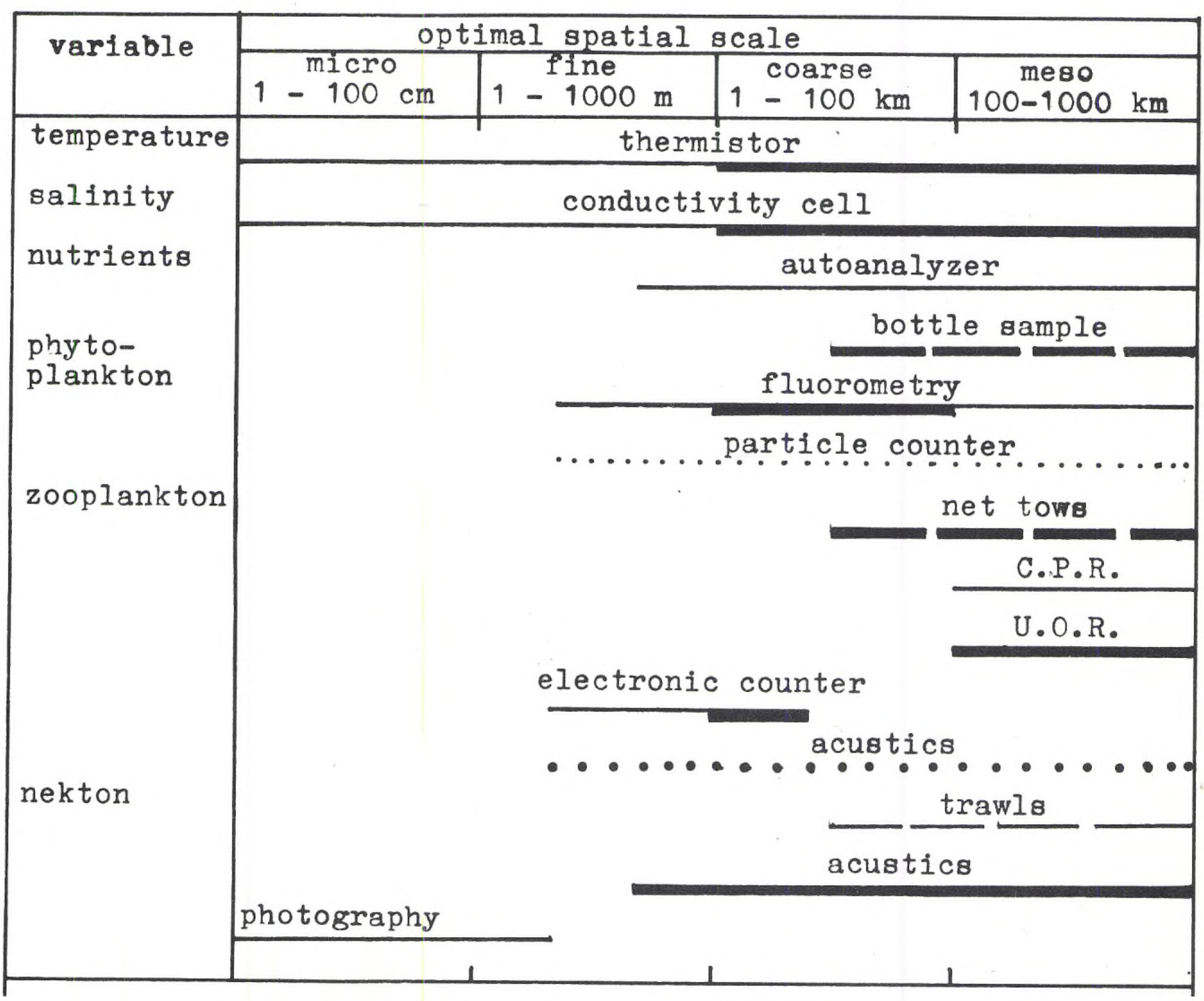

Fig. 6. Sampling windows for patchiness measurements, showing the length scales resolved by various samplers (modified after Denman and Mackas, 1978). - Heavy lines indicate two dimensional sampling. Broken lines indicate poor resolution and/or widely spaced samples. Dotted lines indicate very new or unproven methods. C.P.R. means continuous plankton recorder of Hardy, 1939. U.O.R. means undulating oceanographic recorder of Bruce and Aiken, 1975. "Electronic counter" means the equipment of Herman and Dauphinee, 1980.

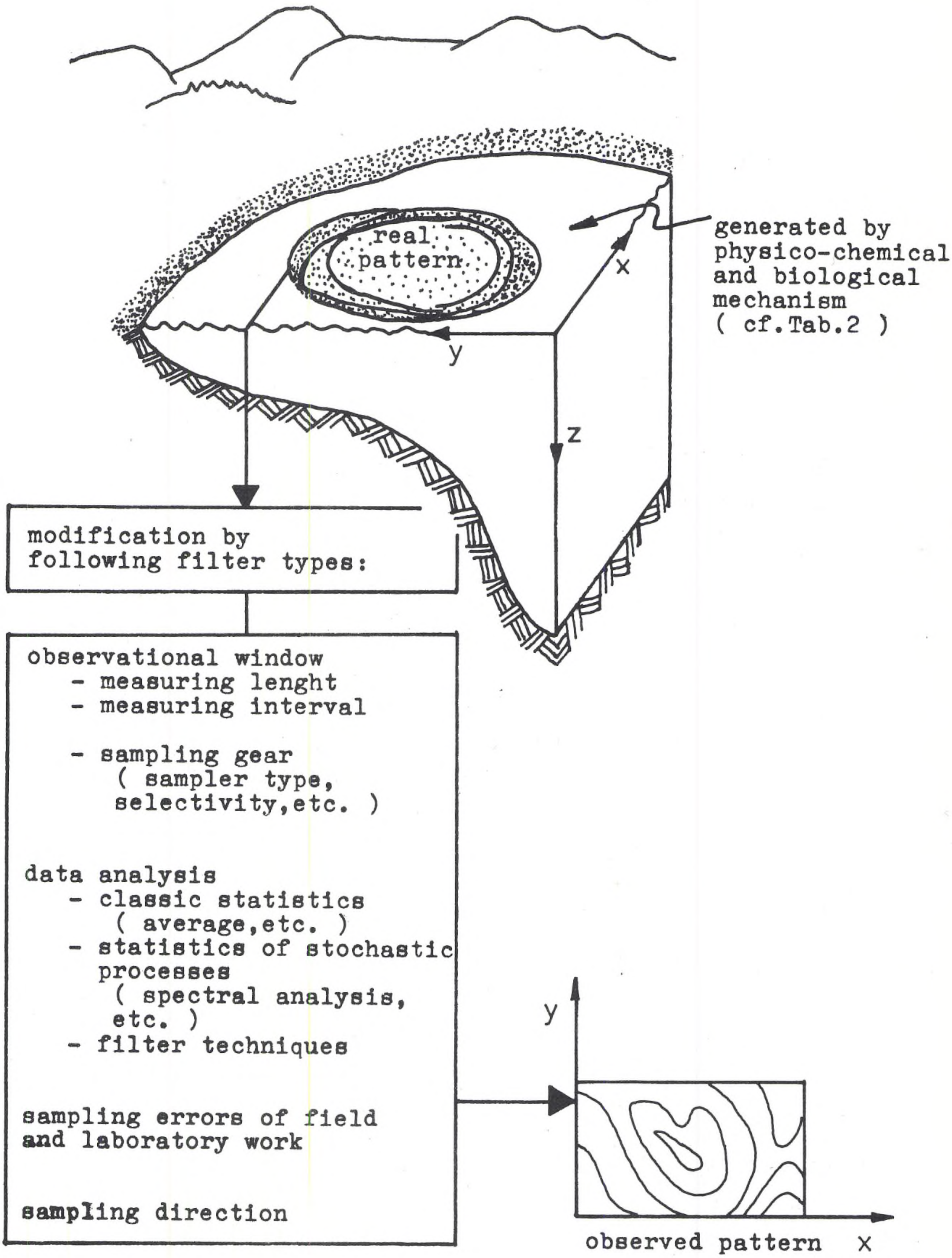

Fig. 7. Main kinds of filters which convert "real patterns" into "observed patterns".